Amendments to the Drawings

The attached 4 sheets of drawings include new Figures 1-4.

The drawing included in the specification has been removed from the specification and is now included as part of Figure 1. Reference numerals have been added.

Figures 1-4 are new but conform to the specification as filed and therefore do not contain new matter.

Attachment: New Drawing Sheets 1-4
Annotated Sheet Showing Additions to Fig. 1 in red from the original drawing included in the specification

Remarks

Objection to the Abstract

The abstract is objected to for being greater than 150 words. The abstract as amended herein is 120 words. Withdrawal of the objection to the Abstract is respectfully requested.

Objections to the Specification

The specification is objected to for incorporation by reference to a publication, and for the layout of the specification.

The specification is amended herein to remove the reference by incorporation.

The references listed in the specification are merely for the convenience of a reader seeking further background information and are not intended to be incorporated by reference into the specification itself. The references are not considered relevant to patentability of the claimed invention.

The specification is amended herein to conform to the layout suggested by the examiner.

The specification is also amended to refer to and describe the new Figures 1-4.

Reconsideration and withdrawal of the objections to the specification are respectfully requested.

Objections to the Drawings

The examiner states the subject matter of this application admits illustration by a drawing, and applicant is required to

provide a drawing. The examiner also objects to the figure, page 2 of the specification, not being a separate drawing.

The figure shown on page 2 of the specification has been removed and forms a separate Figure 1.

The amendment also adds new Figures 2-4 that illustrate features of the invention.

Reconsideration and withdrawal of the objections to the drawings are respectfully requested.

Objections to Claims 33-36

Claims 33-36 are objected to under 37 CFR 1.75(c) as being of improper dependent form for failing to limit the subject matter of a previous claim.

Claims 33-36 are cancelled herein, rendering the objection moot.

Rejections of Claims 18-28 under 35 USC 101

Claims 18-28 are rejected as being drawn merely to an abstract idea that is not tied to a technologic art, environment, or machine, and being no more than manipulation of mathematical equations and data manipulation without any application or tangible output.

Claim 25 is cancelled herein, rendering the examiner's Section 101 rejection moot.

Independent claim 18 is amended herein to recite a method of generating codebook objects for an artificial neural network.

Independent claim 28 is amended herein to recite a method of determining the cluster validity of an artificial neural network.

Independent claims 18 and 28 are methods applied to an artificial neural network to achieve a useful result, and thus claim patentable subject matter.

Based on the foregoing, reconsideration and withdrawal of the Section 101 rejections of claims 18-28 are respectfully requested.

Claims 23-24, 26, 27, and 37-38 are deemed by the examiner to represent a mixing of statutory categories. The claims depend on a method but recite a computer program product or data processing device. Claims 23, 24, 26, 27, and 37, 38 are cancelled herein, thereby rendering the examiner's Section 101 rejections moot.

Rejection of Claims 18-36 under 35 USC 102(b)

Claims 18-36 are rejected under 35 USC 102(b) as being anticipated by Tsuruta et al. "Hypercolumn Model: A Combination Model of Hierarchical Self-Organizing Maps and Neocognitron for Image Recognition" (hereinafter "Tsuruta et al. 2000").

The Hypercolumn Model ("HCM") is a neural network formed as a combination of two different neural networks: the Hierarchical Self-Organizing Map ("HSOM") and the NeoCognitron ("NC").

The HSOM is a multilayer self-organizing map. See Lampinen et al., "Clustering Properties of Hierarchical Self-Organizing Maps", Journal of Mathematical Imaging and Vision 2, pp. 261-272 (1992). A copy of Lampinen et al. is included with the Information Disclosure Statement filed concurrently with this amendment.

An HSOM consists of a first self-organizing map (the first layer) and a second self-organizing map (the second layer), each map having a predetermined number of neurons. The maps become self-organized using the Kohonon algorithm (described in the "Background of the Invention" section of the specification under the heading "Self-Organizing Maps" [which includes paragraphs [012]-[020] of the published patent application]).

For each input vector, the best matching neuron is chosen from the first layer and its index *b* is input to the second layer. The best matching unit for *b* is chosen from the second layer map and its index is the output of the network.

A Neocognitron is a self-organizing neural network used for classifying 2-dimensional visual patterns. See Fukishima, "Neocognitron: A Self-organizing Neural Network Model for a Mechanism of Pattern Recognition Unaffected by a Shift in Position," Biol. Cybernetics 36, 193-202 (1980). A copy of Fukishima is included with the Information Disclosure Statement filed concurrently with this amendment.

The NeoCognitron ("NC") has a 2-dimensional input layer that represents the retina and a number of modular stages or structures that extend "downstream" from the input layer. Each stage extracts appropriate features from the output of the preceding stage and then forms a compressed representation of those extracted features. Classification is achieved by repeatedly extracting and compressing representations until the

input is reduced to a representation the NC has been trained to identify.

Each modular stage is composed of two layers, the S-layer and the C-layer, connected in a cascade. The S-layer extract local features and the C-layer integrate shifted features. Each S-Layer and C-Layer is made up of a predefined number of cells or neurons. Using this structure, the NC reduces dimensionality gradually and can recognize shifted and scaled patterns.

Tsuruta et al. point out that the NC has disadvantages with complex images due to the low reduction rate of the coding scheme and an initial state dependency of competitive learning. The competitive learning used in the NC is not powerful and so for each layer suitable learning data must be generated by hand.

The HCM is constructed by replacing the modular stages of the NC and "pyramidally piling up Lampinen's HSOM similarly to the NC", Tsuruta et al. Section 3.1, page 53. The HSOM layers enable self-organization using Kohonen's SOM algorithm to generate feature maps that preserve the topographic order of the sample data, and to increase the reduction rate of the dimensionality of the feature maps.

Tsuruta et al. Section 3.3 contains pseudocode describing the training process for a feature map in each HSOM layer. The training of the topology-preserving mapping in the HCM is essentially identical to the topology-preserving mapping in the HSOM according to Lampinen et al., that is, both HCM and HSOM use Kohonen's algorithm for self-organization of the neurons.

A brief description of the Kohonen SOM algorithm is given below. The Kohonen SOM is a topology-preserving mapping that exhibits self-organizing effects by its learning scheme.

In the Kohonen SOM algorithm, the data objects of the ordering space (also known as ordering objects or neurons) are determined by a structural hypothesis. "The neurons are arranged to a 1-, 2-, or multidimensional *lattice* such that each neuron has a set of neighbors," Lampinen et al, page 3. In Tsurutu et al. the structural hypothesis was to use one-dimensional maps, although the HCM could use higher-dimensional maps (that is, the HCM could use different structural hypotheses).

Each neuron j of the Kohonen SOM is associated with a weight vector or codebook vector Wj. To self-organize the SOM, all neurons are fed the same input data I. The input data I defines the exploration space of the Kohonen SOM algorithm, that is, the set of data objects with which the topology-preserving mapping is trained. The codebook vectors W define the outcome space resulting from the processing of the input data.

In the Kohonen SOM algorithm the input data I and the codebook vectors W have the same dimensionality, which is independent of the dimensionality of the structural hypothesis defining the neuron lattice. In Tsuruta et al. the dimension of the exploration space is 2 (the HCM described in Tsuruta et al. was trained using a number of two-dimensional images) but the nodes are arranged as a 1-dimensional lattice.

Training the Kohonen SOM to determine the outcome space consists of iterating through the members of the exploration space and presenting each member to all the neurons of the ordering space. In each iteration the best matching neuron is selected (the "winner") and the weights of the codebook vectors of the winning neuron and the neurons in the geometric neighborhood of the winning neuron are adapted. The size of the neighborhood decreases with each iteration, and typically the learning rate decreases as well. Techniques for selecting the winning neuron, defining the neighborhood around the winning neuron, and adaption of the codebook vectors are described in greater detail in the application for the Kohonen SOM algorithm and so will not be repeated here.

The only difference in the Kohonen SOM algorithm used in Lampinen et al. and the Kohonen SOM algorithm used in Tsurutu et al., is that Tsurutu et al. eliminates those neurons that were not selected as a winner in the previous training iteration. As this elimination occurs after the last iteration of the training procedure, i.e. after the training of the HSOM is completed, it is obvious this elimination step is not related to the learning of the HSOM's topology-preserving mapping. It is merely simple "pruning" of non-used neurons after the Kohonen SOM algorithm has been completed.

Two important features of the Kohonen SOM algorithm are first, that the structural hypothesis is independent of the

exploration space, and secondly, that the input data defines the exploration space.

In the Kohonen SOM algorithm the structural hypothesis is independent of exploration space (the set of data being used to train the neurons). "A characteristic of the SOM is that the distance between neurons and the neighborhood for each neuron are defined independently of the data space [input data]," Tsurutu et al. Section 2.1 and quoted by the examiner. Due to the independent definition of the structural hypothesis in the SOM algorithm, the Kohonen SOM algorithm does not determine the order of the neurons in the ordering space by using any of the input data.

In the Kohonon SOM algorithm the input data defines the exploration space, that is, providing input data simultaneously provides the data objects of the exploration space. The input data is iteratively presented to the neurons for generating the codebook vectors. The input data is not used in determining the ordering of the neurons, nor are any other types of data objects used to form part of the exploration space.

Independent claim 18 is rejected as being anticipated by Tsurutu et al. The examiner asserts Tsurutu et al. includes claimed step (d) of "providing data objects, which are required for the data processing, which are <u>independent of the input data</u> to be processed <u>and which are used as data objects of the exploration space</u>" (emphasis added).

The examiner quotes for support for this conclusion Tsurutu et al. Section 2.1, "A characteristic of the SOM is that the distance between neurons and the neighborhood for each neuron are defined independently of the data space". This sentence merely reiterates first characteristic of the Kohonen SOM algorithm referred to above, that the structure hypothesis is independent of the exploration space, and is not related to claimed step (d).

As discussed above, the Kohenon SOM algorithm used in the HCM disclosed by Tsurutu et al. requires that the input data <u>be</u> all the data objects of the exploration space. Tsurutu et al. does not teach or suggest providing data objects which are <u>independent of the input data</u> and which data objects are <u>used as data objects of the exploration space</u> as recited in claim 18.

To clarify this point, Claim 18 is revised herein to recite "(d) providing data objects of the exploration space which are independent of the input data." A non-limiting example of this step as described in the specification would be "...the ordering space can thus be assigned to the input data, and the exploration space can be assigned to the structure hypothesis", see paragraph [0079] of the published specification. Clearly the Kohonen SOM algorithm, in which the input data defines <u>all</u> the data objects of the exploration space does not teach or suggest providing data objects of the exploration space which are independent of the input data (and even if some or all of the input data were also used as data objects of the exploration space).

Independent claim 28 is also rejected as being anticipated by Tsurutu et al. The examiner asserts Tsurutu et al. includes claimed step (ii)(2) of "providing said data objects, that are <u>independent of the input data</u> to be processed and <u>which are used as data objects of the exploration space</u>" (emphasis added). The examiner quotes for support for this conclusion Tsurutu et al. Section 2.1, "A characteristic of the SOM is that the distance between neurons and the neighborhood for each neuron are defined independently of the data space". This sentence merely reiterates first characteristic of the Kohonen SOM algorithm referred to above, that the structure hypothesis is independent of the exploration space, and is not related to claimed step (d).

As discussed above, the Kohenon SOM algorithm used in the HCM disclosed by Tsurutu et al. requires that the input data <u>be</u> all the data objects of the exploration space. Tsurutu et al. does not teach or suggest providing data objects which are <u>independent of the input data</u> and which data objects are <u>used as data objects of the exploration space</u> as recited in claim 28.

Based on the foregoing, reconsideration and withdrawal of the Section 102(b) rejections of independent claims 18 and 28 are respectfully requested. As dependent claims 19-22 and 29-32 depend from allowable claims 18 or 28, reconsideration and withdrawal of the Section 102(b) rejections of claims 19-22 and 26-32 are also respectfully requested.

Claims 23-27 and 33-38 are canceled herein, rendering the Section 102(b) rejections moot. Applicant reserves the right to present these claims in a divisional application.

Conclusion.

Correction of applicant's name and entry of this amendment are solicited.

This amendment places the application in condition for allowance. If issues remain, the examiner is invited to telephone the undersigned to discuss resolution of same.

Respectfully submitted,

AXEL WISMÜLLER

By Jeffrey S. Habib

Jeffrey S. Habib
Attorney of Record
Reg. No. 42,615

Hooker & Habib, P.C.
100 Chestnut St., Ste. 304
Harrisburg, PA 17101
(717) 232-8771